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Review papers

Design considerations for riverine floods in a changing climate – A review

B. François*, K.E. Schlef[1], S. Wi, C.M. Brown

Department of Civil and Environmental Engineering, University of Massachusetts Amherst, Amherst, MA 01003, USA

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ABSTRACT

Conventional methods for designing infrastructure that is subject to flood risk, such as dams and levees, assume a stationary design flood. However, observed and potential non-stationarity in floods can result in costly over-design or dangerous under-design. Despite substantial attention, evidence from the literature makes clear there is no consensus methodology for estimating design variables under climate change. Practical guidance remains elusive. This paper presents a review of the challenges and advances in design of infrastructure for floods under non-stationarity. First, potential sources of non-stationarity in time series of floods are described to provide context and motivation. Second, methods for estimating design floods that rely on the stationary assumption are presented and their limitations are discussed. Third, methods for estimating design floods that assume non-stationarity resulting from climate change are summarized. Finally, the inadequacies of current design methodologies in view of the pervasive uncertainties are assessed and strategies to manage the consequences of those uncertainties are presented.

1. Introduction

Infrastructure such as dams and levees are built to reduce risk from hydrological extremes such as riverine floods. Conventionally, such infrastructure is designed to protect against flood events up to a chosen magnitude. This so-called *design flood* is commonly defined as the flow quantile with a selected frequency of occurrence or return period. For example, the 100-year return flood is typical for designing levees and other protection structures (e.g., Olsen, 2006). More recently, the design value is sometimes chosen based on maximizing net economic benefits (i.e., avoided damages by implementing flood protection less the cost of the protection) or minimizing the expected damages of flooding (e.g., Lund, 2002). For infrastructure where failure would lead to tremendous damages, such as very large dams, some national and regional agencies use the concepts of Probable Maximum Precipitation or Flood (PMP or PMF) rather than statistical approaches for design (WMO, 2009). All of these approaches to design flood estimation make use of the assumption of stationarity.

Notably however, stationarity lacks a well-established definition within the hydrologic and water system analysis literature. For instance, Milly et al. (2008) described stationarity as "*the idea that natural systems fluctuate within an unchanging envelope of variability*". Montanari and Koutsoyiannis (2014), referencing Kolmogorov (1931, 1938) and Khintchine (1934), defined as stationary a process that "*undergoes change, but its statistics are conserved*". Other studies, such as that by Salas et al. (2018), maintain that stationary means "*the marginal distribution remains invariant in time*". In this review, we adopt the definition by Salas et al. (2018). In the context of design for riverine floods, this definition of stationary implies that the design flood is time-invariant and hence the probability of infrastructure failure remains constant for the duration of the design life.

There is now a significant body of literature claiming that it is no longer valid to assume the design flood is stationary. This claim is based on theoretical considerations and observational evidence from some locations that flood risk is changing due to climate change and socio-economic development (e.g., Dankers et al., 2014; Winsemius et al., 2015; Arnell and Gosling, 2016; Berghuijs et al., 2017 and references within). While *flood risk* combines hydrological hazard and vulnerability (Merz et al., 2010), here the focus is hydrological hazard, which is the probability of occurrence of a given flood magnitude. The concern is that if the design flood is indeed nonstationary, then an assumption of stationarity could result in over- or under-design (Jain and Lall, 2001; Rosner et al., 2014). Over-design occurs when infrastructure becomes too large as peak flows decrease, leading to sunk capital and operating costs. Conversely, under-design occurs when infrastructure becomes too small as peak flows increase, leading to societal impacts such as human casualties and economic damages, which are generally of higher concern than sunk costs (Rosner et al., 2014). For instance, the American

* Corresponding author.
E-mail address: bfrancois@umass.edu (B. François).
[1] Now at: Consortium of Universities for the Advancement of Hydrologic Science, Inc., Cambridge, MA 02140, USA.

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Society of Civil Engineers estimates that about $150 billion in flood damages resulting from Hurricane Katrina were due to under-design of levees and other flood protection structures (ASCE, 2007).

To avoid over- or under-design, Hirsch (2011) recommends that *"once we recognize that we have nonstationarity for a variety of reasons,* […], *we really have to rethink our approach to planning*". This quote summarizes the increasingly common motivation to improve current and develop new design approaches that account for non-stationarity in hydro-meteorological processes, and thus improve the robustness and resilience of flood infrastructure (Beven, 2011; Kundzewicz et al., 2017). For example, in 2010, a workshop in Boulder (Colorado, U.S.) gathered hydrologists, climatologists, engineers and scientists around the question: "*if stationarity is dead, what do we do*?" (Galloway, 2011). One topic was whether the U.S. federal guidelines for Flood Frequency Analysis, as described in Bulletin 17B (IACWD, 1982), should be updated to account for non-stationarity. Eight years later, the update, Bulletin 17C, acknowledges evidence of non-stationarity but provides no concrete guidance for its incorporation into analysis and design, instead suggesting that in situations of sufficient evidence for climate-induced non-stationarity, water practitioners should "*employ time-varying parameters or other appropriate techniques*" (England Jr. et al., 2018).

However, water practitioners do not generally know the range of available methods for flood frequency analysis assuming non-stationarity (Serinaldi and Kilsby, 2015) even though the use of such approaches and models have gained popularity in academia (e.g., Strupczewski et al., 2001; Delgado et al., 2010; Katz, 2013; Prosdocimi et al., 2014; Yu et al., 2015; Spence and Brown, 2016; Šraj et al., 2016; see Salas et al., 2018 for a review). This lack of knowledge likely stems from the proliferation of approaches and the many challenges associated with assuming non-stationarity. Challenges include but are not limited to: comprehensively diagnosing the drivers of change (e.g., anthropogenic climate change or natural climate variability) (Vogel et al., 2011; Deser et al., 2012a; Elmer et al., 2012; Merz et al., 2012; Harrigan et al., 2014), determining how change affects the flood time series (e.g., when a trend is detected, a statistically significant mean shift can also be detected) or distribution moments (i.e., mean, variance, skewness and kurtosis; although, in practice, observational records are too short to detect changes in the latter two) (Coles, 2001; Xiong and Guo, 2004; Villarini et al., 2009a; Katz, 2013), and identifying appropriate mathematical models to represent change (e.g., multiple mathematical models have been used to represent change in annual maximum flows at the Little Sugar Creek (Charlotte, North Carolina), leading to widely different estimates of the 100-year flood) (Villarini et al., 2009b; Salas and Obeysekera, 2014; Serinaldi and Kilsby, 2015).

This paper addresses the need for guidance on design for riverine floods under non-stationarity, particularly as associated with climate change, by providing a comprehensive review of available design methods and guidelines. Section 2 reviews the main drivers that can lead to changes in peak flow magnitude and frequency and then discusses methods commonly used for detection of change and attribution to specific drivers. Section 3 reviews the available stationary approaches to design flood estimation and provides an example application with record of flood events showing non-stationarity. Section 4 describes current methods for estimating the design flood assuming non-stationarity. Section 5 discusses the available options for addressing uncertainty. Section 6 concludes with an outlook on future flood design and further research.

2. What assumption should be made?

The question of whether to assume a stationary or non-stationary design flood is closely tied to considerations of the spatiotemporal scales associated with the natural and anthropogenic processes that drive flood events and the intended infrastructure design (Fig. 1).

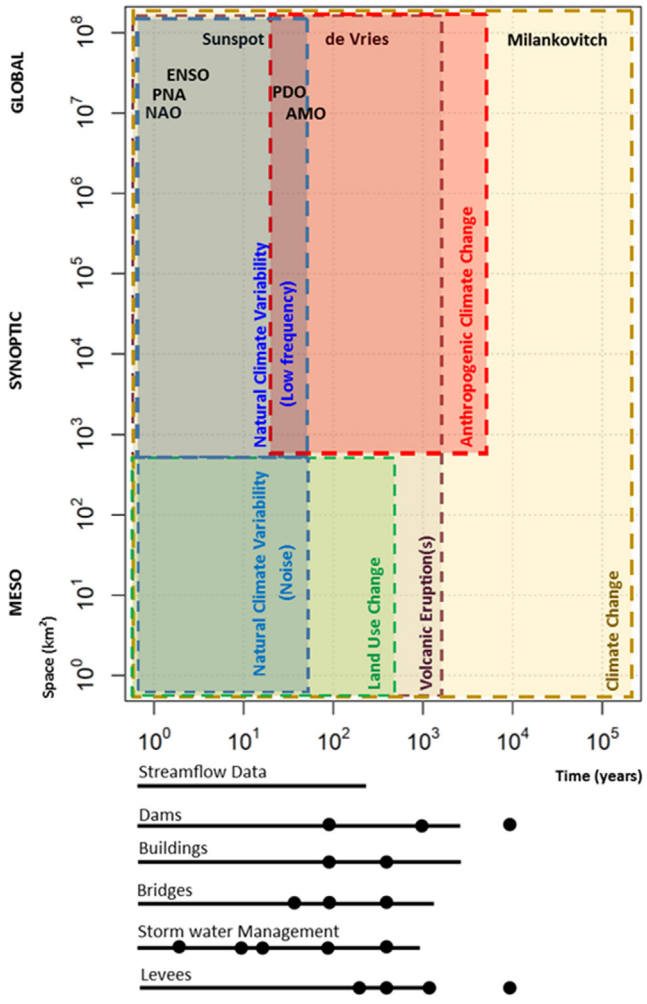

Fig. 1. Generalized spatiotemporal scales for selected flood drivers (boundaries and placements are approximate). The examples of low-frequency oscillatory ocean-atmospheric phenomena are meant to be illustrative, not exhaustive (NAO is the North Atlantic Oscillation, PNA is the Pacific/North American pattern, ENSO is the El Nino-Southern Oscillation, PDO is the Pacific Decadal Oscillation, and AMO is the Atlantic Multidecadal Oscillation). For each infrastructure type, the solid line shows the possible lifespan (the upper bound was set to be approximately the age of the oldest existing and in-use element to-date) while the dots indicate common flood return periods used in design (the PMF, commonly used for dams, is approximated by the 10,000-year return period); the time scale of streamflow data records is shown for comparison. Climate change is defined (following the glossary of IPCC, 2014) as the combined influence of natural climate variability, anthropogenic climate change, changes in land use, volcanic eruptions, and solar cycles.

Clearly, the processes acting on the timescale of the design event for a storm water management system (e.g., 10-year flood) are vastly different from those acting on the timescale of a PMF used for dam design. In this context, this section explores: (1) potential non-stationarity induced by processes driving flood events, (2) methods for detecting change in peak flow series, and (3) methods for attributing observed change to specific drivers. The discussion is supported further by examples to illustrate the issues associated with the range of spatiotemporal scales that influence the magnitude and occurrence of flood events as well as their detection and attribution to particular drivers.

2.1. Evidence and drivers of non-stationarity in riverine floods

Riverine floods are primarily driven by (1) precipitation, which is driven by natural climate variability (e.g., Deser et al. 2012a) and

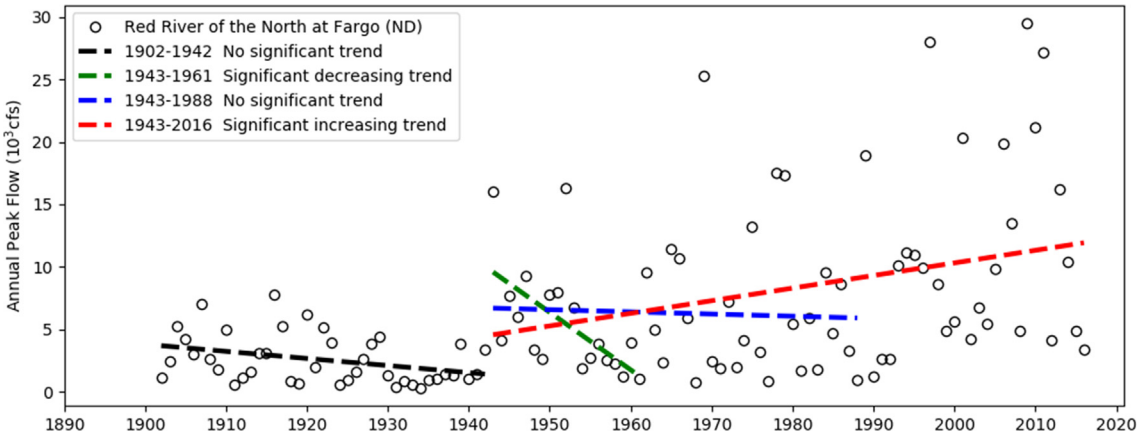

Fig. 2. Annual peak flow for the Red River of the North at Fargo (North Dakota, USA) (USGS id: 05054000) Dashed curves show trends for different periods (discussed in Section 2.2). The significance of the trends has been tested against the null-hypothesis of an i.i.d. process with the Mann-Kendall test at the 5% significance level. Flow values are in cubic feet per second (cfs). Note that Villarini et al. (2009a) detected a significant shift in mean peak flow in 1942. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

anthropogenic climate change (e.g., Zhang and Delworth, 2018), and (2) land surface response, which is driven by land-use change, river regulation, and natural catastrophes. Each of these drivers are potential sources of non-stationarity. The Red River of the North at Fargo (North Dakota, U.S.) is a particularly salient example of nonstationary stream flow (Fig. 2) (Mueller and Foley, 2014). Although flagged as regulated by the U.S. Geological Survey, the U.S. Army Corps of Engineers (USACE) demonstrated that changes in streamflow beginning in the early 1940's (Villarini et al., 2009a) cannot be explained by flow regulation (see discussion in Serinaldi and Kilsby, 2015); instead, tree ring analysis has shown that the river experiences "*high and low flood modes […], which extend from several decades to nearly a century*" (George and Nielsen, 2003).

Natural climate variability, sometimes called internal climate variability, is "*variability of the climate system that occurs in the absence of external forcing, and includes processes intrinsic to the atmosphere, the ocean, and the coupled ocean–atmosphere system*" (Deser et al., 2012b). Natural climate variability, generally considered to occur on timescales of 30 years or less (with exceptions), is comprised of two components acting at different spatiotemporal scales; (1) noise at local and regional scales and (2) low-frequency oscillations at regional to sub-global scales that have a global influence on hydrology (Deser et al., 2012a; Hulme et al., 1999). For example, the El Nino-Southern Oscillation (ENSO) occurs in the tropical Pacific but influences hydrology around the globe (Trenberth, 1997; Ward et al., 2014; Lee et al., 2018). Natural climate variability can affect flood magnitude (e.g., Hannaford and Marsh, 2008; Schlef et al., 2018a; Zhang et al., 2015), frequency of occurrence (e.g., Andrews et al., 2004; Delgado et al., 2012; Hodgkins et al., 2017; Kiem et al., 2003; Mallakpour and Villarini, 2016a), and timing (e.g., Blöschl et al., 2017) (for other examples of the influence of natural climate variability of floods see also Petrow et al., 2009; Prudhomme and Genevier, 2011; Villarini et al., 2013; Wilby and Quinn, 2013; Armstrong et al., 2014; Li and Tan, 2015; Bracken et al., 2018). Natural climate variability is generally thought to cause temporal clustering or semi-cyclical patterns in floods (e.g., Jain and Lall, 2001).

Anthropogenic climate change is forcing of the atmosphere by anthropogenic greenhouse gas emission, leading to global-scale changes in the coupled ocean-atmospheric system (IPCC, 2014). Notably, in model simulations, natural climate variability dominates the signal in precipitation and temperature due to anthropogenic climate change until around 2050 (Hawkins and Sutton, 2011; Deser et al., 2012b; Hingray and Saïd, 2014; Whateley and Brown, 2016; Schlef et al., 2018b; Martel et al., 2018). At the horizon 2050, natural climate variability may still be difficult to separate from anthropogenic climate change effects on integrated variables such as streamflow and crop yields (e.g., Hulme et al., 1999). There is physically-based evidence that ongoing anthropogenic climate change may lead to an intensification of and changes in the water cycle worldwide (IPCC, 2014), leading to changes in floods (e.g., Milly et al., 2002; Hirabayashi et al., 2013; Kundzewicz et al., 2013; Alfieri et al., 2015; Arnell and Gosling, 2016). Warmer air temperatures will increase atmospheric moisture holding capacity, leading to an increase in the intensity and variability of extreme precipitation (Lenderink and Meijgaard, 2008; Trenberth, 2011; Berg and Haerter, 2013; Fischer and Knutti, 2016; Yin et al., 2018), likely affecting flash and short-rain floods (for flood definitions here and subsequently, see Merz and Blöschl, 2003). Warmer temperatures will also cause snowpack accumulation to shrink in mountainous regions and at high latitudes (Barnett et al., 2005) and change the timing and rate of snowmelt (e.g., McCabe and Clark, 2005; Blöschl et al., 2017; Musselman et al., 2017). In general, these modifications are likely to decrease rain-on-snow and snowmelt floods, but are dependent on local trends. Additionally, there will be changes in storm tracks and individual storm intensities, linked to changes in the underlying large-scale circulation patterns (Bengtsson et al., 2006; Boé and Terray, 2008; Knutson et al., 2010; Santos et al., 2016; Shaw et al., 2016), likely affecting short- and long-rain floods. Apart from the possibility of a tipping point, anthropogenic climate change is generally thought to produce slow and long-term trend-like changes in floods.

Land use changes include urbanization, forest management, and agricultural practices, which can affect floods for up to several centuries but can only be verified at spatial scales up to several tens of square kilometers (Blöschl et al., 2007; Rogger et al., 2017). In particular, the expansion of impervious areas due to urbanization decreases infiltration, which weakens the buffering effect of the natural ecosystem, causes changes hydrological extremes (e.g., Rose and Peters, 2001; Smith et al., 2002; Konrad, 2003; Moglen and Shivers, 2006; Saghafian et al., 2008; Villarini et al., 2009a,b; Vogel et al., 2011). Land use changes are thought to cause either change points or trend-like changes in floods.

River regulation (or training) can range from construction of dams and weirs to straightening meandering or braided rivers. The impacts of river regulation on floods varies (for one example of the magnitude of impact see Vorogushyn and Merz, 2013); for large rivers, the effects of river regulation on floods may be as much or greater than land use changes (Lammersen et al., 2002; Bronstert et al., 2007). In the case of channel modification, the impact is largest when the flood remains in the riverbed (Hall et al., 2014). River regulation is generally thought to introduce change points in floods.

Natural catastrophes, in particular volcanos, cause immediate and massive impacts at local and regional scales, cause global cooling and

changes in hydrology in the first several years after the event, and may contribute to long-lasting and global climate change under certain conditions (Hofmann, 1987; Major and Mark, 2006; Schneider et al., 2009; Trenberth and Dai, 2007). Natural catastrophes are generally thought to introduce change points in floods but are not generally considered in non-stationary analyses.

2.2. Detection of change in peak flow records

Tracking or anticipating change in hydrologic extremes is the typical starting point when considering the adequacy of the current flood risk management strategy at a given location. There are a variety of methods available for detecting trends and shifts in hydrological time series (see the reviews by Kundzewicz and Robson, 2004; Khaliq et al., 2009; Madsen et al., 2014; Bayazit, 2015). The World Meteorological Organization (WMO, 2009) recommends the non-parametric Mann-Kendall test for trend analysis (MK; Kendall, 1975); it does not require an assumed probability distribution, has been widely applied to hydrologic extremes (e.g., Petrow and Mertz, 2009; Petrow et al., 2009; Villarini et al., 2009b; Mediero et al., 2014; Archfield et al., 2016), and has been adapted to account for long-term persistence (Hamed, 2008). For detecting shifts, the non-parametric Pettitt test (1979), which is easily implementable, has been widely used (e.g., Villarini et al., 2009a; Rougé et al., 2013; Prosdocimi et al., 2014; Li and Tan, 2015; Mallakpour and Villarini, 2016b). However, it only detects one shift within a time series; unlike the Rodionov test (2004).

These and other methods do not always correctly detect trends and shifts, as illustrated by simulation experiments where the trend is stochastically generated (Spence and Brown, 2016) and is highly dependent on spatiotemporal scale (Fig. 1). Specifically, the outcome of statistical tests for trend detection depends on the hydrological record length (Blöschl and Montanari, 2010; Barros et al., 2014). Using the Red River of the North at Fargo as an example (Fig. 2), we applied the MK test to three periods: the first (1943–1961) shows a significant downward trend, the second (1943–1988) shows no significant trend, and the third (1943–2016) shows a significant upward trend. Although these periods were obviously chosen specifically to illustrate the point, this analysis indicates that the overall trend was dominated by low-frequency variability for several decades. This example highlights that natural climate variability has its own structure, which can easily confound trend analysis. Although temporal and spatial structures of certain climate patterns are relatively well characterized (e.g., ENSO), this emphasizes the importance of diagnosing the structure of natural variability and adapting the trend analysis. For instance, if temporal clustering or semi-cyclical patterns are identified in peak streamflow, one solution is to apply trend tests over periods that include one or more cycles (Ishak et al., 2013). At longer timescales, the Hurst phenomenon (Hurst, 1951), in which a trend may not be separable from persistence, applies (Koutsoyiannis, 2003, 2006). The outcome of the statistical tests also depends on spatial scale and may vary from one catchment to another (Archfield et al., 2016) in part due to land-use change or regulation (Vogel et al., 2011). Aggregation to large spatial scales tends to reduce the noise of natural climate variability and improves trend detection (Fischer and Knutti, 2014).

2.3. Attribution of change in peak flow records

Attribution, which consists of quantifying the contribution of various drivers to change in peak flows, is crucial for projection (Hall et al., 2014) and can raise awareness of the need for mitigation (e.g., Thompson and Otto, 2015; Schwab et al., 2017). Attribution studies of changes in hydro-climatic extremes in general and of the causes of individual events (e.g., Allen, 2003; Pall et al., 2011, 2017; Easterling et al., 2016; Viglione et al., 2016) are becoming more common. For flood change attribution, Merz et al. (2012) suggested a three-part framework that uses observed peak flows and simulation results. The first part, *evidence of consistency*, relates to whether the observed change in peak flows is consistent with change in the assumed driver. The second part, *evidence of inconsistency*, consists of demonstrating that change in peak flow is not the outcome of a different driver from the one originally assumed; the aim is to avoid wrong attribution when several drivers of changes are acting at the considered location. The third part is the *provision of confidence* level of the causality attribution. This framework is often reduced to comparing observed peak discharges with simulated discharges that are obtained with and without changes in the drivers (e.g., Wolski et al., 2014; Aich et al., 2015; Prosdocimi et al., 2015) (see Section 4.1.2 for a description of possible statistical approaches). The drawback of this causal framework and other sensitivity-type analyses are that inference is limited to the relative or qualitative weights for various drivers and is limited when several drivers are jointly responsible for changes in peak flows (Harrigan et al., 2014; Vogel et al., 2011).

2.4. Implication for design

The above sections highlight that clear physical reasoning supports non-stationarity in floods. However, physical evidence is often inconclusive. Natural climate variability and land use change make detection and attribution of change difficult, which could at least partly explain the lack of physical evidence. Thus, engineers and decision-makers could find a trend but not be sure if it is due to anthropogenic climate change. Alternatively, they may find no trend but since the climate change signal is yet to be detected, flood hazard may nevertheless increase or decrease in the future. In either case, these possibilities pose a clear design challenge. The sections below discuss the limitations of current approaches given this context.

3. Status quo: design flood assuming stationarity

The stationarity assumption has been used for decades for designing flood infrastructure and has been demonstrated to be the most pertinent assumption at many locations (Serinaldi and Kilsby, 2015; Luke et al., 2017). Assuming stationarity, there are two primary approaches to determining the design flood (Fig. 3). The first is to perform Flood Frequency Analysis (FFA) and then use pre-determined return periods

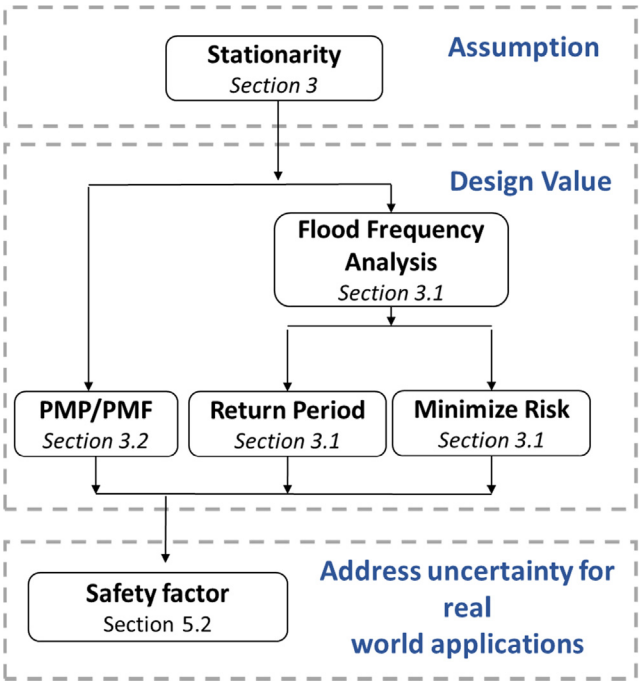

Fig. 3. Pathway of choices for flood design under stationary assumption.

or risk-based approaches. The second is to use the concept of PMP and PMF. This section briefly reviews these methods.

3.1. Design based on flood frequency analysis

In stationary FFA, observed peak flow values are represented by a probability distribution with time-invariant parameters:

$$\boldsymbol{Y} \sim f(\theta_1, ..\theta_k, ..,\theta_K), \quad (1)$$

where $\boldsymbol{Y} = (y_1, y_2, ..y_N)$ is the peak flow time series, N is the number of observations, '~' means 'distributed as', and f is a chosen distribution function. The U.S. recommends the log Pearson type 3 distribution (England Jr. et al., 2018) and the National Environment Research Council in the United Kingdom recommends the Generalized Extreme Value distribution (NREC, 1975); other extreme value distributions may also be appropriate (Merz and Theiken, 2009). $\theta = (\theta_1, ..,\theta_K)$ is a vector of K parameters (usually $K = 2or3$). For more details on conducting FFA assuming stationarity, including parameter estimation, application to ungauged catchments or at regional scales, and handling missing data, the reader can refer to the aforementioned guidelines and the reviews by Coles (2001), Katz et al. (2002), and Khaliq et al. (2006). Uncertainty in FFA is introduced in streamflow measurements and in fitting extreme value distributions to limited records.

Once FFA is complete, there are two approaches to determining a design value. The first approach is to use a pre-determined return period. The 100-year return flood, in particular, has become commonly used in the U.S. as "*a reasonable compromise between the need for building restrictions to minimize potential loss of life and property and the economic benefits to be derived from floodplain development*" (FEMA, 2011), partially due to the National Flood Insurance Program, which mandates flood insurance for structures at risk of the 100-year flood. However, the choice of flood protection standard may be more political than based on scientific or economic justification. For example in the U.S., the 500-year standard mandated after Hurricane Sandy by the Obama administration was subsequently reversed by the Trump administration (Koerth-Baker, 2017). The degree of conservatism varies by country. In the Netherlands, standards for levee and dike design, which range anywhere from the 300- to 10,000-year flood depending on location, were developed from FFA of historic data and the analysis of costs of construction compared to damages and risk of death associated with past floods (Voorendt, 2015). The second is a risk-based approach that minimizes total expected cost (National Research Council, 2000; Lund, 2002; Jonkman et al., 2004; Tung, 2005). In practice, the objective is to balance the costs of protection with the expected costs associated with the hydrological hazard (i.e., flood damage costs plus the costs of any emergency actions taken during the flood event). Thus, the assumption of stationarity applies to not only the flood probability distribution, but also the socio-economic estimates that determine infrastructure and damage costs, which add another level of uncertainty.

3.2. Probable maximum precipitation and flood

A significant part of the flood design literature relies on the concept of PMP and PMF. PMP is "*the greatest depth of precipitation for a given duration meteorologically […] with no allowance made for long-term climatic trends*" (WMO, 1986). The PMF is the flood that would result from the combination of the PMP and the most severe hydrologic conditions (i.e., initial soil moisture and/or snowpack) considered physically possible in the region. The PMF is used for designing infrastructure whose failure would cause tremendous damages to the downstream population and economy (e.g., large dams). Its return period has sometimes been associated with values ranging from 10^4 to 10^7 years (Fernandes et al., 2010; Nathan et al., 2016). It is primarily used in North America and Australia; most European countries use conventional FFA (Boes, 2011), because such high return periods are considered beyond the credible limit of extrapolation (Nathan and Weinmann, 2001). In the U.S., state-level regulations sometimes allow design within a range; the lower bound may be set by either a return period (e.g., the 500-year flood) or a percent of the PMF, while the upper bound is a percent of the PMF (FEMA, 2012).

The World Meteorological Organization provides guidelines for estimating PMP (WMO, 2009). According to those guidelines, there are two distinct categories of methods; those based on the statistical analysis of observed extreme rainfall and those that rely on physically-based storm modelling. The WMO recommends the statistical analysis of extreme rainfall (Hershfield, 1961) as an approximation for PMP for small catchments with surface area less than 1000 km^2. The most common physically-based approach, called storm maximization and storm transposition (e.g., Rakhecha et al., 1999), consists of boosting the atmospheric conditions (most often the atmospheric moisture) to the physical limits. More specifically, the PMP_T value for a storm of duration T at a given location can be obtained by (Stratz and Hossain, 2014):

$$PMP_T = Pobs_T \left(\frac{W_p(max)_T}{W_p(obs)} \right), \quad (2)$$

where $Pobs_T$ is the maximum observed depth of precipitation for the duration T at the location of the observed storm, $W_p(obs)$ is the precipitable water in the air column of the actual storm being maximized, and $W_p(max)_T$ is the maximum probable precipitable water in the moisture column in the transposed location where PMP is estimated. Several methods exist for estimating the latter. For instance, the USACE estimates $W_p(max)_T$ based on the maximum 12-hour persisting temperature dew point (Schreiner and Riedel, 1978). Another method is to define $W_p(max)_T$ as the 100-yr return precipitable water estimated from numerical simulations (e.g., a regional climate model) (Beauchamp et al., 2013). In Eq. (2), PMP_T is defined for the same duration and for the same area as the observed storm. This value can be interpolated to another spatial area and another duration by using depth-area-duration curves (U.S. Department of Commerce, 1999).

The PMP is converted into the PMF using either a hydrological model or the unit hydrograph method. These methods require as input the Maximum Probable Storm (PMS), which is the hypothetical storm for a particular drainage area and duration that results from the PMP. The PMS temporal structure is commonly obtained by assuming a hyetograph specific to the climatic region (for the continental U.S., see Water Resources Program, 2009). The PMS spatial pattern is usually based on a standard isohyetal pattern that has a shape and orientation corresponding to that commonly observed at the location (National Weather Service, 1982). The PMF estimate is sensitive to both initial soil conditions and to the spatial and temporal patterns of the PMS, leading to uncertainty bounds that may be as large as 50% (Jakob, 2013). In locations where PMF is likely to occur during periods when snowmelt may significantly contribute to runoff, it is recommended to assume a 100-year return period snowpack (Debs et al., 1999; Beauchamp et al., 2013); additional uncertainty is introduced in estimating the snowpack.

3.3. Concerns in the use of traditional methods with non-stationarity

If the drivers discussed in Section 2 cause non-stationarity in hydrological extremes, the use of a stationary FFA or PMP/PMF may lead to poor design estimates (e.g., Jain and Lall, 2001; Sarewitz et al., 2003; Kunkel et al., 2013; Rosner et al., 2014). Poor design estimates can occur for reasons such as (1) the available historic data may only partially sample the range of peak flow variability resulting from low-frequency oscillations associated with natural climate variability or (2) a trend detection test may provide a false positive or false negative. To illustrate how non-stationarity can affect the design flood estimate, we use the example of the Red River of the North at Fargo. We fit the Generalized Extreme Value distribution (GEV; Jenkinson, 1955) for two

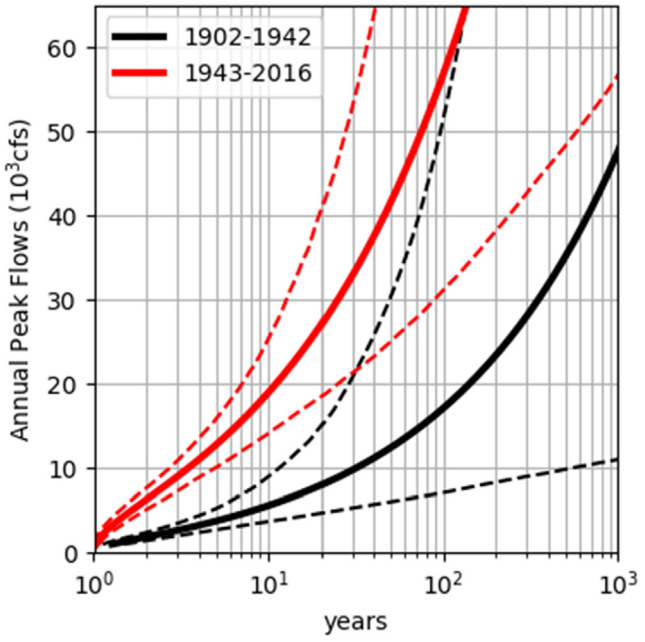

Fig. 4. Flood frequency curves for the Red River of the North at Fargo (USGS id: 05054000) as obtained prior and after the year 1942 GEV parameters are calibrated regarding the observed peak flows by optimizing the maximum likelihood function (Martins and Stedinger, 2000). 90% confidence intervals (dashed lines) are obtained via bootstrap method (Obeysekera and Salas, 2014) . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sub-periods of the annual maximum streamflow records (1902–1942 and 1943–2016). Fig. 5 displays the flood frequency curves for these two periods, together with their confidence intervals as obtained via bootstrap (Obeysekera and Salas, 2014). The peak flow quantiles obtained from the period 1902–1942 are significantly different from those from 1943 to 2017. Let us assume that, in 1942, local engineers designed a levee based on the 100-year flood. According to the available data (1902–1942), the design flood equals $17*10^3$ cfs. However, this value was surpassed ten times during 1943–2017 (Fig. 4), which would have potentially caused significant societal consequences. On the flood frequency curve obtained with the 1943–2016 data, the $17*10^3$ cfs corresponds approximately to an 8-year flood. Using data from 1942 to 2016, the 100-year flood equals $57*10^3$ cfs and corresponds to a 1500-year return period according to the 1902–1942 data. This example illustrates how the use of FFA assuming stationarity may lead to under- or over-design should the peak flow distribution change.

4. Nonstationary design flood estimation

This section describes the primary approaches to flood projection and subsequent design flood estimation under non-stationarity (Fig. 5). These approaches are often referred to as 'Predict-Then-Act' approaches in the sense that predicted change in flood quantiles are used for infrastructure design (Lempert et al., 2004). This section focuses on anthropogenic climate change and natural climate variability because they are major sources of non-stationarity in the peak flow distribution or the PMP/PMF, although the overarching concepts are also relevant for changes in land-use and river regulation.

4.1. Design based on flood frequency analysis under non-stationarity from climate

Assuming non-stationarity, the first step in design flood estimation via FFA is projection of flood risk; here the focus is on projection of the flood distribution, although projection of future infrastructure cost and flood damages is also necessary for risk assessment. There are two primary approaches to projection of the flood distribution; (1) hydrologic simulation approaches combine simulation output from General Circulation Models (GCMs) with downscaling and bias correction methods and hydrological modeling (green box in Fig. 5) and (2) informed parameter approaches create statistical models with time-varying parameters (blue box in Fig. 5). The latter include trend-informed models in which time is the only covariate and climate-informed models in which climate variables are used as covariates.

4.1.1. Flood projection via hydrologic simulation approaches

Climate projections from GCMs are often used for assessing future changes in river flows through a chain of models. GCMs are physically-based models that attempt to consistently simulate the behavior of the atmosphere, land-surface and ocean, including interactions among these components, at a global scale. Scenarios that attempt to span the range of plausible future greenhouse gas emissions (CMIP3 experiment, Nakicenovic et al., 20001) or concentrations (CMIP5 experiment, Taylor et al., 2012) drive GCM projections of future climate variables. Because GCM outputs are subject to biases (e.g., Dai, 2006; Kundzewicz and Stakhiv, 2010; Sillmann et al., 2013; Crétat et al., 2014) and are simulated at spatial resolutions that are coarser than the scale required by the hydrologic models to represent the paramount processes generating runoff (Fowler et al., 2007), the outputs are commonly bias corrected and downscaled to create realistic inputs for hydrologic models (Maraun et al., 2010). The downscaled and bias corrected GCM projections are then used to force physical or conceptual hydrologic models to simulate extreme streamflow.

Use of this approach is wide-spread and ranges from the catchment scale (e.g., Camici et al., 2014; McMillan et al., 2010; Ngongondo et al., 2013; Prudhomme et al., 2003) to national, continental and global scales (e.g., Alfieri et al., 2015; Arnell and Gosling, 2016; Dankers and Feyen, 2009; Dankers et al., 2014; Hirabayashi et al., 2008, 2013; Leng et al., 2016; Rojas et al., 2011, 2012; Roudier et al., 2016). The major advantage of using the chain of models is that the evolution of flood-inducing weather variables under future atmospheric conditions is physically modeled. However, this framework suffers from several shortcomings discussed below (e.g., Kundzewicz and Stakhiv, 2010), and overall is subject to a myriad of sources of uncertainty that arise from each step of the modeling framework (Stainforth et al., 2007a; Wilby and Dessai, 2010).

The use of GCM projections for assessment of hydrological extremes is questionable because GCM estimates of precipitation are biased, particularly in extremes (e.g., Mehran et al., 2014) which affects simulation of hydrological processes (e.g., Leander and Buishand, 2007; Sperna Weiland et al., 2010; Rocheta et al., 2014). In particular, GCMs do not simulate the physical processes that generate extreme precipitation that trigger most flood events because those processes occur at spatial scales that are finer than model resolutions (e.g., Boberg et al., 2007; Leander and Buishand, 2007; Wuebbles et al., 2014; Crétat et al., 2014). In comparison to observations, historical simulations usually underestimate precipitation extremes, which suggests an underestimation of projected precipitation extremes (Kundzewicz et al., 2017), likely resulting in an underestimation of future peak flows.

Bias correction and downscaling, which sometimes involves implicit bias correction, are common approaches to mitigating the bias and coarse resolution of GCM outputs, with the goal of producing more hydrologically-relevant projections of climate. Bias correction is the *"correction of model output towards observations in a post-processing step"* (Ehret et al., 2012). Bias correction methods have multiple disadvantages: (1) bias is corrected without consideration of the forcing or structural errors which may be causing the bias, (2) bias in statistics other than the mean, such as the variance, is often not corrected (Teutschbein and Seibert; 2012), and (3) bias is assumed time-invariant (i.e., bias identified in the current period can be used to correct bias in future periods), which can cause misleading results when assessing

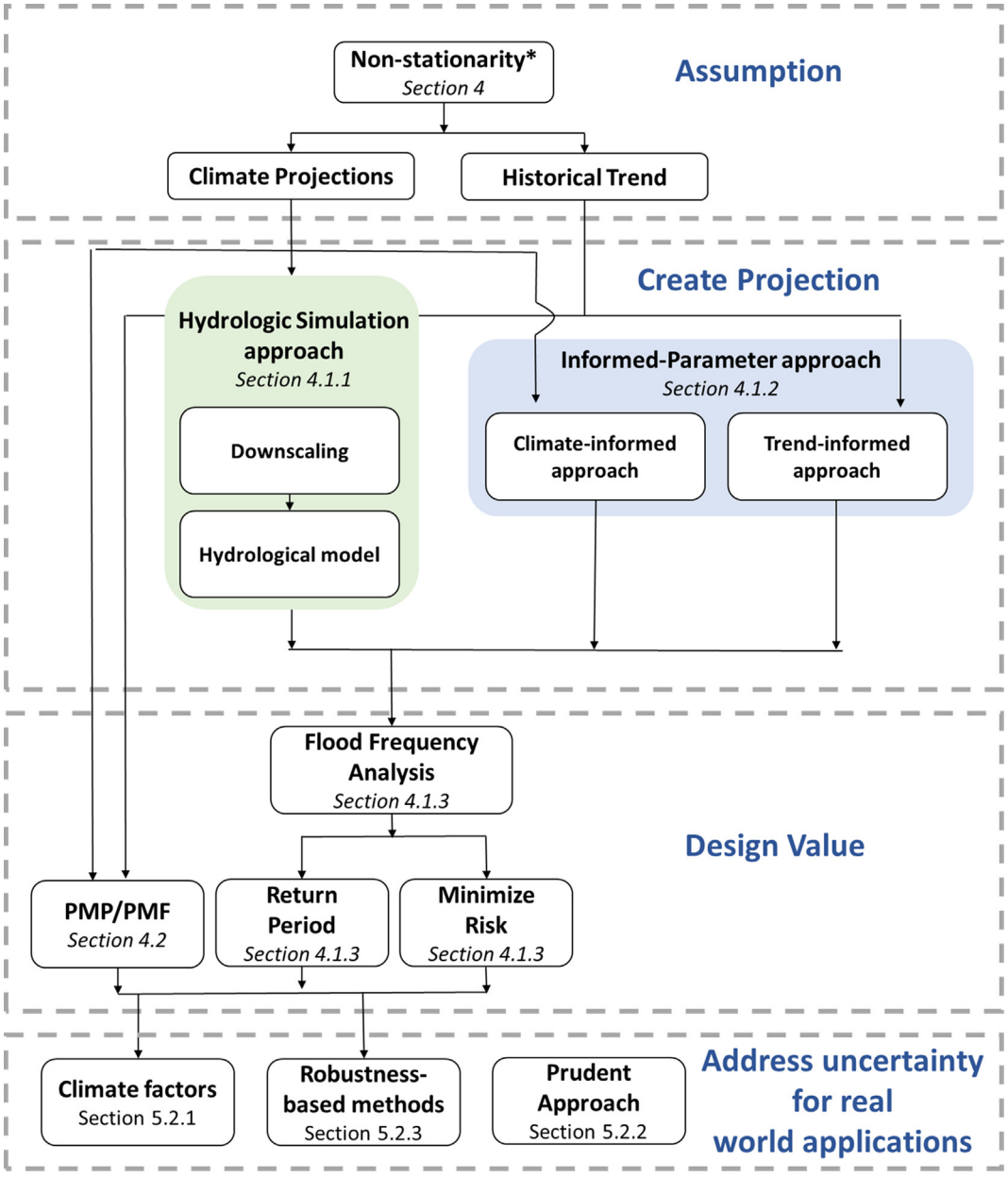

Fig. 5. Pathway of choices for flood design under nonstationary assumption (*only accounting for climate variability and change).

hydrological extremes (e.g., Ehret et al., 2012; Maurer et al., 2013; Velázquez et al., 2015). Thus, bias correction alone is not recommended for future flood design.

Downscaling methods can be classified into three main categories: (1) delta change factor methods (or perturbation methods), (2) statistical methods, and (3) dynamical methods (Ekström et al., 2015; for comprehensive reviews see also Fowler et al., 2007; Madsen et al., 2014). Delta change factor methods perturb observed time series of precipitation and temperature with changes identified by GCM projections (e.g., Prudhomme et al., 2002, 2003; Lehner et al., 2006; Kay et al., 2006), more sophisticated variations of this method can account for seasonal effects and changes in variability (e.g., Hingray et al., 2007; Willems and Vrac, 2011). Statistical downscaling methods include (1) regression methods, which rely on multivariate statistics representing the link between large-scale climate predictors and local predictands (e.g., Bürger and Chen, 2005; Hessami et al., 2008), (2) resampling methods such as weather typing and climate analogs, which rely on the relationship between synoptic meteorological patterns and local predictands (e.g., Boé et al., 2006; Lafaysse et al., 2014; Pierce et al., 2014; Raynaud et al., 2017), and (3) stochastic weather generators, which simulate time series of chosen weather variables reproducing observed or pre-defined statistics or patterns conditioned on large-scale or synoptic circulations (e.g., Qian et al., 2002; Chen et al., 2018). Finally, dynamical downscaling methods consist of using Regional Climate Models (RCMs) which are similar to GCMs but have higher resolution and smaller modeling domains (see Rummukainen et al., 2010; Xue et al., 2014 for reviews). Because RCMs produce their own bias in addition to inheriting bias from GCM boundary conditions, RCM projections are commonly further bias corrected and downscaled (Sunyer et al., 2012).

For analysis of possible future design floods, delta change factors are not recommended because they do not account for local differences that exist within the same GCM grid cell and for any feedback processes (Ekström et al., 2015). The computational cost associated with the use of RCMs is still sufficiently high to limit the temporal span of projections, reducing confidence in subsequent FFA. Also, RCM projections

are usually available for only a few GCM/RCM realizations, and thus do not span the range of GCM internal variability. Rather, use of an ensemble of statistical methods is recommended, for two reasons. First, no single method out-performs others in intercomparison studies of statistical downscaling methods (Bronstert et al., 2007; Gutiérrez et al., 2018); thus, it is impossible to definitively choose one method. Second, downscaling contributes as much, if not more, uncertainty as the forcing scenario and GCM model (Bürger et al., 2013; Hingray and Saïd, 2014; Lafaysse et al., 2014); thus, it is necessary to estimate the uncertainty through the use of an ensemble. Regardless of what downscaling methods are chosen, it is crucial to evaluate the resulting climate scenarios for their climatic credibility and plausibility (i.e., are current climate conditions well-represented and is the realization of possible future climate physically sound) as well as their relevance and quality for hydrologic impact analysis (Bronstert et al., 2007).

The bias corrected and downscaled climate projections are then used to drive hydrologic models to simulate streamflow at a given location (e.g., Hingray et al. 2014). Although the comparison of different hydrologic models has a long-standing history in hydrology (e.g., Refsgaard and Knudsen, 1996), the implications of hydrologic modeling choices for assessing changing environmental conditions has recently emerged as a concern (e.g., Merz et al., 2011; Brigode et al., 2013; Mendoza et al., 2015). Hydrologic modeling choices, as discussed by Mendoza et al. (2016), include assuming time-invariant model parameters, model structure (e.g., Chen et al., 2013; Wi et al., 2015), the spatial resolution of input data (e.g., Lobligeois et al., 2014; Essou et al., 2016), the existence of multiple optimal parameter sets (e.g., Wi et al., 2015), calibration and validation periods (e.g., Coron et al., 2012, 2014) and the calibration objective function. Studies that have examined the effect of these choices on flood projection have found that while the importance of different sources of uncertainty varies by hydrologic regime and return period (Kay et al., 2009), the uncertainty from future climate can be as much or more than the uncertainty from the model structure (Booij, 2005; Steinschneider et al., 2015a) and that estimates of the 100-year can vary widely depending on the combination of modeling choices (Brigode et al., 2015; Wi et al., 2015). Due to the uncertainty stemming from hydrologic models, an ensemble of model structures and parameter sets is recommended, the latter could be inferred using various calibration and validation periods. If computational constraints make an ensemble undesirable, a simple sensitivity analysis could indicate the magnitude of uncertainty stemming from hydrologic models relative to GCMs and downscaling methods; if the hydrologic model uncertainty is of comparable or greater magnitude, then the ensemble should be reconsidered.

4.1.2. Flood projection via informed parameter approaches

Informed parameter approaches use statistical models with time varying parameters to allow the flood distribution to be nonstationary (e.g., Serago and Vogel, 2018); in other words, Eq. (1) becomes $\boldsymbol{Y}(\boldsymbol{t})\ f(\theta_1(t), ..,\theta_K(t))$ and provides a peak flow distribution for each time step (usually annual) out to the planning horizon; for the most recent and exhaustive review of nonstationary statistical methods, see Salas et al. (2018). There are two main approaches. The first, termed the *trend-informed approach*, makes use of the historical trend to model non-stationarity in the peak flow distribution (e.g., El Adlouni et al., 2007; Rootzén and Katz, 2013; Salas and Obeysekera, 2014; Luke et al., 2017). The second, termed the *climate-informed approach* (e.g., Sankarasubramanian and Lall, 2003; Kwon et al., 2008), is to model the temporal evolution of the flood distribution parameters using large-scale climate variables as covariates. A common practice is to try a variety of models (e.g., either trends or covariates for various distribution parameters or moments) and retain the best model, often assessed using a criterion such as the Akaike or Bayesian information criterion. However, assessment of the best model should also consider whether the modeled changes can be linked to physical processes and whether those links will remain valid under future climate conditions (e.g., Jiang et al., 2016). For example, a time-varying location parameter could correspond to changes in moisture content of storms and their intensity (Stedinger and Griffis, 2011) while a time-varying scale parameter could correspond to changes in storm features (e.g., winter storm vs. snowmelt).

In the trend-informed approach, model parameters are:

$$\theta_k(t) = \sum_{n=0}^{N} a_{k,n} t^n, \tag{3}$$

where $\theta_k(t)$ is the value of the k^{th} parameter of the flood distribution for time t, $a_{k,n}$ are regression coefficients, and N is the regression order. Usually N equals 1 (i.e., linear relation) or 2 (i.e., quadratic relation). The trend-informed approach has been primarily used to model non-stationarity in the historical period for characterizing historical changes (e.g., Strupczewski et al., 2001; Delgado et al., 2010; Vogel et al., 2011; Prosdocimi et al., 2014; Šraj et al., 2016; Hu et al., 2017).

The use of the trend-informed approach for assessing future design values relies on the questionable assumption that historical trends will remain the same over the entire planning period (Jain and Lall, 2001; He et al., 2006; Sivapalan and Samuel, 2009; Blöschl and Montanari, 2010; Serinaldi and Kilsby, 2015; Luke et al., 2017). In an analysis of 1250 stream gauges across the U.S., trend-informed models were rarely preferred even when a trend was detected in the first half of the record because it rarely persisted into the second half; however, for gauges where the physical processes underlying the trend did continue, an *updated* stationary model, which used the parameters of the trend-informed model at the end of the first half of the record, was generally preferred (Luke et al., 2017). Additionally, trend-informed models are often limited by sampling uncertainty and model structure uncertainty and robustness; for example, two models with comparable goodness-of-fit for the historical period can lead to significantly different flood quantiles for future periods (Serinaldi and Kilsby, 2015). Given these limitations, a high level of caution is needed when using trend-informed models to assess future flood design values.

Climate-informed model parameters are:

$$\theta_k(t) = \sum_{m=1}^{M_k} \sum_{n=0}^{N_{k,m}} a_{k,m,n} x_{k,m}^n(t), \tag{4}$$

where $x_{k,m}$ is the value of the m^{th} climate covariates at time t for the parameter $\theta_k(t)$,and $a_{k,m,n}$ are the regression coefficients. Compared to Eq. (3), the time variable has been replaced by covariates $x_{k,m}$, which are usually large-scale climate variables, but can also be non-climatic, such as a reservoir index (López and Francés, 2013) or carbon dioxide concentrations (Hirsch and Ryberg, 2012). The number of climate covariates will depend on the parameter and the regression order will depend on both the parameter and the number of covariates.

Implementing climate-informed models requires identifying the relevant climate patterns and/or variables that drive flood occurrence and magnitude over the study region. The choice of the relevant covariates usually follows from analysis of the hydro-climatology, scientific literature, and historic reports for the considered area (e.g., Delgado et al., 2012; Schlef et al., 2018a). In the case where identification of covariates is not straightforward, there are a variety of available methods: time series correlation (e.g., Kwon et al., 2008), correlation maps (e.g., Schlef et al., 2018a), composite analysis (e.g., Jain and Lall, 2001), weather typing (e.g., Robertson et al., 2015), simulation experiments (e.g., Cook, 1999), and use of a Bayesian frameworks to identify spatial patterns in gridded data (Renard and Lall, 2014). Projections of the covariates to drive changes in flood distribution parameters are usually obtained from GCMs (blue box on Fig. 2). This requires the covariates to be well reproduced by GCMs, thus favoring covariates defined over large spatial domains and at monthly to seasonal temporal scales rather than daily localized precipitation used to force hydrologic models. For instance, maximum annual precipitation over a region should not be used as covariate because of low GCM skill

(e.g., Boberg et al., 2007; Leander and Buishand, 2007; Wuebbles et al., 2014; Crétat et al., 2014). Similar to downscaling approaches (e.g., Greene et al., 2011), the use of both thermodynamic and dynamic covariates is expected to increase model robustness under climate change.

Climate-informed models have been used for analyzing or reconstructing historical variability of hydrological extremes (e.g., Griffis and Stedinger, 2007b; Kwon et al., 2008; Li and Tan, 2015; Bracken et al., 2018) and for projecting future peak flow (Delgado et al., 2014; Tramblay et al., 2014; Condon et al., 2015; Schlef et al., 2018a). Similar to the hydrologic simulation approach, the credibility of flood projections derived from climate-informed models is subject to limitations and uncertainties stemming from the use of GCMs, but unlike the simulation approach, avoids the uncertainty stemming from downscaling methods and hydrological models. Although GCM performance regarding highly-studied climate patterns such as ENSO and PDO is generally acceptable and well-characterized (e.g., Taschetto et al., 2014; Yim et al., 2015), this may not be the case for other climate variables relevant to a specific gauge location, such as soil moisture (Yuan and Quiring, 2017). Furthermore, GCMs often do not correctly reproduce correlations between climate patterns (e.g., Kim et al., 2017) and calculation of some large-scale climate indices from GCM outputs can be prohibitively difficult. Projections from climate-informed models are also highly influenced by the choice of covariates, which depends on the modeler's experience and knowledge of the study area and even the best combination of covariates is unlikely to fully explain peak flow variability (e.g., Delgado et al., 2012). Finally, uncertainty stemming from sampling, model structure, and robustness of covariates under future climate remains poorly characterized (e.g., Merz et al., 2014). Despite these limitations, climate-informed models are a relatively new and appealing alternative to flood projection via hydrologic simulation.

4.1.3. Nonstationary return periods and risk assessment for design

The definition of nonstationary return periods is still an area of ongoing research and discussion. Flood projections derived from trend-informed models can use a revised concept of return period, defined as the mean expected time from the current date to the first occurrence of a flood event that exceeds the chosen design value (Cooley, 2013; Salas and Obeysekera, 2014) or equivalently, the time length for which the probability of exceedance is one (Parey et al., 2007). Calculation of this revised return period requires that time-varying probabilities of exceedance be summed to infinity (Eq. (4.3). in Cooley, 2013) and that the temporal evolution of flood events be correctly represented. This revised return period cannot be applied to projections derived from either the hydrologic simulation approach or climate-informed models because they do not meet those two conditions (i.e., most of the GCMs project climate for the next century only and cannot predict the temporality of events). Consequently, return periods for flood projections derived not using a trend-informed model are often calculated assuming stationarity within a chosen time window (e.g., 1950–2000 for a historic period and 2050–2100 for a future period) (Schlef et al. 2018a), which re-assumes stationarity and imposes short record lengths (e.g., 50 years) from which to calculate extreme values (e.g., the 100- or 500-year flood). Alternatives to either the revised return period or re-assuming stationarity include the *design life level*, which is the probability of the event occurring within the planning horizon (Rootzén and Katz, 2013), and reliability, which is the probability that an exceedance event will not occur over the planning period (i.e., expected performance, rather than expected failure) (Read and Vogel, 2015). Once nonstationary flood probabilities have been determined from the flood projections, as in the stationary case, design can be based on either predetermined return periods or a risk-based approach (e.g., Schlef, 2018). Frequently, nonstationary risk-based approaches are embedded into sequential decision frameworks, such as a decision tree (cf. Loucks et al., 2005), to infer sequential adaptation measures (e.g., Manning et al., 2009; Gersonius et al., 2013; Rosner et al., 2014).

4.2. Probable maximum precipitation and flood under non-stationarity from climate

Whether the PMP and subsequent PMF are likely to change at a given location is a subject of controversy. Jakob (2013) for instance highlighted a subtle change in the PMP definition in the most recent WMO guidelines (i.e., 2009 compared to 1986). The new definition states that "*PMP is the theoretical maximum precipitation for a given duration under modern meteorological conditions*", which emphasizes that the PMP may have changed in the past and could be modified in the future should the climate change. To date, there are no federal guidelines for dam design that account for potential changes in PMF, perhaps due to the perspective that "*there is no compelling evidence that would support climate-related changes in PMFs*" and that current design recommendations should be changed only when substantial research quantitatively demonstrates a link (USACE, 2016). However; recent academic research using both climate projections and historical trends, although still nascent, indicates there likely is a link. Significant increases in PMP have been shown for the whole contiguous U.S. (Kunkel et al., 2013), specific locations within the U.S. (Stratz and Hossain, 2014; Gangrade et al., 2018), and specific locations in Canada (Rousseau et al., 2014; Clavet-Gaumont et al., 2017). Regardless, to-date no method has become widely acknowledged for projection of future PMP and PMF under climate change, and thus we are unable to offer guidance on specific methods.

5. Addressing design flood uncertainty

At the most basic level, uncertainty in design flood values can be broadly conceptualized as being comprised of two components: *aleatory* uncertainty is essential, unavoidable unpredictability or chance (i.e., the residual unpredictability of events given models and parameters), while *epistemic* uncertainty is lack of knowledge or ignorance (i.e., roughly, lack of confidence about parameters and models) (Spiegelhalter & Riesch, 2011). However, the complexity of climate change has led to the concept of *deep* or *severe* uncertainty, which *"results from myriad factors both scientific and social, and consequently is difficult to accurately define and quantify"* (Kandlikar et al., 2005; for more discussion see also Lempert et al., 2004; Hall et al., 2007; Hall et al., 2012; Ray and Brown, 2015). Both aleatory and epistemic uncertainty are present under the assumption of stationarity; deep uncertainty is added under the assumption of non-stationarity. This section first describes uncertainty quantification and attribution, and then describes methods for incorporating uncertainty into design.

5.1. Uncertainty quantification and attribution

A common approach to quantifying aleatory and epistemic uncertainty is through confidence intervals (e.g., dashed curves in Fig. 4), which have long been a topic of active research in hydrologic science (e.g., IACWD, 1982; Stedinger 1983; Ashkar et al., 1987; Hu, 1987; Schendel et al., 2015; England Jr. et al., 2018). Under stationarity, confidence intervals are generally obtained through the variance of the design quantiles (e.g., Lu and Stedinger, 1992). Under non-stationarity, assessment of confidence intervals is less straightforward. Obeysekera and Salas (2014) described three methods: (1) a delta method, which is "*based the large sample properties of maximum likelihood estimators",* (2) a bootstrap method, which is *"based on the bootstrap of standardized data, which are then used to fit an ensemble of nonstationary models"* and (3) a profile likelihood method from Coles (2001), which *"uses the* log-*likelihood function"*; the delta and bootstrap methods are more computationally efficient but less accurate compared to the profile likelihood method.

For lack of a better approach, quantification of deep uncertainty has been generally based on the use of ensembles of forcing scenarios, initial conditions, and models or methods (e.g., the ensembles of GCM

projections in IPCC, 2014). In this case, the spread of the ensemble is considered to provide some, albeit limited and usually underestimated, indication of the level of associated uncertainty (Stainforth et al., 2007b). There is significant research effort aimed at reducing ensemble spread by improving models; however, significant reductions are only possible with hundreds if not thousands of additional years of observations (Leach 2007). Alternatively, other efforts aim to achieve a more informative ensemble spread by selecting GCMs which demonstrate good performance or are independent (Knutti et al., 2013; Steinschneider et al., 2015b). However, since non-independent GCMs are more likely to project changes toward the same direction and/or with comparable magnitude, the use of an increasing number of non-independent models into an ensemble could lead to an apparent reduction of the uncertainty, although this reduction is likely to be meaningless (Knutti, 2010). The use of ensembles has led to many attribution studies (e.g., Hawkins and Sutton, 2009; Hingray and Saïd, 2014), which use methods of sensitivity analysis, such as ANOVA, to partition to the total uncertainty as represented by the ensemble spread, into portions attributable to specific sources, which may include forcing scenario, initial conditions, model structure, model parameters, etc. (Stainforth et al., 2007a).

5.2. Incorporating uncertainty into design

Under the assumption of stationarity, the common engineering approach to incorporating uncertainty in design is through safety factors; or freeboard in the context of levee or dam design, which in some cases is even applied to the already conservative PMF (e.g., FEMA, 2012; Shaw, 2009; NYC rules, 2013). Notably, such safety factors are usually independent of the confidence interval estimation of uncertainty, which is not generally used in design; as stated in Bulletin 17C, "*application of confidence intervals in reaching water-resource planning decisions depends upon the needs of the user*" (England Jr. et al., 2018) and proposed approaches are generally limited to research applications. If, for example, the risk of under-design must be reduced to 5%, a possible approach, although naïve, could be to use the value of the upper bound of 90% confidence interval could be used. While this use is straightforward and can easily be applied in practice, it overinterprets the mathematic definition of the intervals (e.g., Klemeš, 2002; Serinaldi and Kilsby, 2015). Another proposed use entails a cost-benefit analysis to determine a design value which accounts for epistemic uncertainty arising from parameter estimation (Botto et al., 2014, 2017; Gaume, 2018).

Under the assumption of non-stationarity, particularly as arises from climate change, there are three primary means of incorporating uncertainty in design: climate factors (i.e., the application of an additional safety factor specifically addressing the uncertainty from climate change), the prudent approach (i.e., use of information that is known with relatively high confidence to qualitatively inform whether additional protection should be considered in design) and robustness-based decision methods (i.e., finding a design which is satisficing over a wide array of plausible futures). As a side note, taking the (weighted) mean of the ensemble, which is an approach commonly used to summarize the oftentimes overwhelming amount of information from future climate projections, serves only to conceal the uncertainty and negatively impact characterization of extremes, rather than actively incorporate that uncertainty into design.

5.2.1. Climate factors

In the context of uncertainty associated with climate change, additional safety factors are called climate allowances or climate factors. Through a review of existing guidelines in Europe, Madsen et al. (2014) found that the use of climate factors with the explicit purpose of protecting against climate change is rare; exceptions include Germany, Norway, and the United Kingdom (Defra, 2006; Hennegriff et al., 2006; Lawrence and Hisdal, 2011; Environmental Agency, 2016). Although climate factors are easy to apply, such a "*simplistic adjustment to peak flow estimates*" is a result of "*poorly understood impacts of future climate change*" (e.g., Kuklicke and Demeritt, 2016). Climate factors lack flexibility because they are generally prescribed for a single time-horizon (one exception is the recent United Kingdom guidelines) and incorrectly estimate small-scale variability because they are usually defined by basin or political boundaries (Madsen et al., 2014). Calculation of climate factors is generally described in technical reports, which often lack clear descriptions of calculation methods and are based on the difference between historical and projected simulations of streamflow from GCMs. Furthermore, studies that assess climate factor performance are limited but needed, especially given that the resulting climate factors can be highly sensitive to the modeling choices (e.g., the first-generation of United Kingdom climate factors, see Reynard et al., 2005; Defra, 2006; Prudhomme et al., 2010).

5.2.2. Prudent approach

Even under deep uncertainty, the direction of change of some key variables can be known with relatively high confidence; for example, temperature has and will continue to increase under climate change. This information can be used to qualitatively infer the likely direction of change in hydrological extremes (e.g., decreased snowpack would lead to smaller and earlier peak flows, or intensified extreme precipitation will increase peak flows), assuming sufficiently negligible feedback effects. Given this information, decision-makers might decide to opt for a prudent approach, based on the precautionary principle (Gollier and Treich, 2003). In the context of climate change mitigation, Kirkwood (2011) noted that "*the prudent path lies somewhere between doing absolutely nothing about climate change and doing everything possible*". In the context of decision-making for hydrologic design, the prudent approach consists of making design decisions based on expected changes in peak flows or their drivers that are known with relatively high confidence. The prudent approach is especially applicable for projects involving discrete choices, such as levee height or the size of a pump station. For example, given a discrete set of return periods used for design, if the 50-year flood was initially selected, but there was high confidence that future peak flows would increase, the prudent approach would choose the next discrete level, such as the 100-year flood. This is often justifiable when its marginal cost is small compared to the total infrastructure cost (Hallegate, 2009). An even more precautionary approach to flood risk, adapted by the Scottish Environment Protection Agency, is to prohibit development of flood sensitive projects in medium to high risk areas (SEPA, 2017).

5.2.3. Robustness-based decision methods

To deal with deep uncertainty associated with climate change, Lempert (2002) introduced the idea of robustness. Unlike a risk-based approach, which finds an optimal design for one assumed future state of the world, a robustness-based approach finds a design that will be satisficing (i.e., perform well, Simon, 1956) for a large range of plausible futures. Multiple approaches using the concept of robustness have been developed: Robust Decision Making (Lempert, 2003), Info-Gap analysis (Ben-Haim, 2006), Scenario-Neutral approach (Prudhomme et al., 2010), and Decision Scaling (Brown et al., 2011, 2012). Stakhiv (2011) provides an extended discussion on the use of robust-decision making methods for water resource management under climate change. Both Info-Gap analysis and Decision Scaling have been specifically applied to design of flood infrastructure (Hine and Hall, 2010; Steinschneider et al., 2015a; Spence and Brown, 2016, 2018; Knighton et al., 2017) and the Scenario-Neutral approach has been applied to determine system vulnerability to hydrological extremes without prescribing a design value (Prudhomme et al., 2010). Despite the value of robustness-based decision methods, quantitative approaches to their implementation are relatively new and require increased application and improvement. For example, Hall et al. (2012) showed that Info-Gap and Robust Decision Making provide similar but not identical solutions for the same case study, yet note that the comparison improved

understanding of the system and the proposed management options.

6. Discussion and conclusion

This paper addresses the need for guidance on design for riverine floods under non-stationarity. In particular, Section 2 addresses evidence and drivers of non-stationarity as well as methods for detection and attribution. The key points are:

- Theoretical reasons/historical evidence indicate that flood hazard is possibly changing at some locations due to climate change
- For design of short-life infrastructure (< 30 years), the natural climate variability signal dominates the anthropogenic climate change signal; consequently, assuming stationarity may be adequate, but long historical records are recommended for inferring model parameters
- For design of long-life infrastructure (> 30 years), the assumption of stationarity may not be valid due to anthropogenic climate change impacting the magnitude, occurrence and typology of floods
- The structure inherent in natural climate variability can confound trend analysis and should be diagnosed and addressed, when possible.
- Methods for detecting change are imperfect; however, this effect can be reduced through regionalization and using long historical records

Section 3 addresses status quo flood design, which assumes stationarity. The key points are:

- Design of long-life infrastructure is usually based on either (1) FFA with pre-specified return periods or risk minimization or (2) the concepts of PMP and PMF
- If flood hazard is indeed nonstationary, the status quo can lead to costly over-design or dangerous under-design

Section 4 addresses methods for nonstationary flood design under climate change. The key points are:

- For nonstationary flood design, FFA must use projections from either hydrologic simulation or informed-parameter approaches; such projections rely on GCM projections of future climate which often have biased precipitation estimates and unknown future skill
- For the hydrologic simulation approach:
  - o Bias correction alone and delta change downscaling methods are not recommended
  - o Use of the projections currently available from RCMs are not recommended because the simulation periods are often too short to estimate flood frequency. The small number of GCM/RCM realizations does not allow a correct representation of the range of GCM internal variability.
  - o The use of GCM projections can be improved through statistical downscaling but use of an ensemble of downscaling methods and evaluation of method credibility is recommended because no one method outperforms others and because downscaling adds considerable uncertainty
  - o Ensembles of hydrologic models are recommended in cases where the ensuing uncertainty is comparable to or greater than that from GCMs and downscaling methods. A sensitivity analysis could be used to infer the relative contribution of hydrological models to the total uncertainty
- For informed-parameter approaches:
  - o Trend-informed models are not recommended for projection because historical trends will not necessarily persist during the entire planning period
  - o Climate-informed models are an appealing alternative to hydrologic simulation, but are still a relatively new and untested methodology, and should be used as a complementary approach
- Nonstationary return periods are difficult to define and provide minimal design guidance; instead, the concepts of design life level and reliability, which transparently communicate probability of failure, are recommended for guiding design
- Since studies of changing PMP and PMF are nascent and no clear and well-established methods for assessing change exist, no method is recommended, despite the possibility that PMP and PMF are nonstationary under climate change

Section 5 addresses quantification and attribution of design flood uncertainty, and approaches to incorporating uncertainty associated with climate change into design. The key points are:

- Aleatory and epistemic uncertainty are present under the assumption of stationarity; deep uncertainty is added in the context of nonstationarity from climate change
- Confidence intervals are recommended for communicating aleatory and epistemic uncertainty, although their use for design is often unclear; ensembles are recommended for characterizing deep uncertainty, despite indicating only the lower bounds of the full uncertainty range
- For design, robustness-based decision methods are recommended to account for climate change uncertainty; if a robustness-based approach is not possible, the use of either climate factors or prudent approach should be considered

Some very clear, and relatively unsurprising, avenues of needed future research arise from this review. First, future research should aim to cultivate non-traditional sources of data that can be used to extend observed records, such as historical information (e.g., written records) and paleo-data (e.g., tree rings and sediment cores), and generate improved future records (e.g., satellite data and crowd-sourced streamflow measurement). Second, given the strengths and weaknesses of methods for flood hazard projection for FFA, future research should focus on improved understanding of the climate processes driving floods, more applications of the climate-informed approach, and methods for assessing the potential credibility of projections under climate change. For PMP and PMF, future research should address uncertainty reduction for PMP and PMF and development of methods for projection that can be widely accepted. Finally, more research is needed on application and evaluation of methods for incorporating (deep) uncertainty into design.

To conclude this discussion about design considerations under nonstationarity, specifically in the context of climate change, it is worth quoting Jakob (2013): "*Design with change in mind. Not just climate. Think across disciplines*". Whether stationarity is "*dead*" (Milly et al., 2008), "*alive*" (Lins and Cohn, 2011), "*immortal*" (Montanari and Koutsoyiannis, 2014) or "*undead*" (Serinaldi and Kilsby, 2015) is not really important provided that the chosen approach to design can sufficiently represent the physical system and its evolution. The ultimate goal is robust (or even resilient) design that avoids both sunk capital costs and massive flood damages. Thus, when inference from climate projections lack significant change in flood drivers over the design horizon, the stationarity assumption may be preferred. However, in the presence of observed or theoretical evidence that flood hazard is changing or is likely to change in the future, then the non-stationarity assumption may be preferred. While this review focused on climate change, non-climatic factors also can cause changes in flood hazard, possibly on shorter time scales.

The impact of both climate and non-climate factors on flood hazard signals the *"end of the static design paradigm"* (Brown, 2010). This implies that the chosen design may fail more quickly than expected; hence the growing focus on resilient design across many disciplines, including flood design (e.g., Park et al., 2011; Sayers et al., 2012). Additionally, this implies that design should be able to tolerate various levels of failure, rather than existing solely in binary failure or non-failure states,

meaning that non-structural flood solutions should be designed conjunctively with structural solutions. Finally, while a static infrastructure design may be optimal for the most likely future in a risk-based approach or satisficing for most plausible futures in a robustness-based approach, the end of static design promotes adaptive flood risk management which benefits from increasing knowledge through time (e.g. Hui et al. 2018). Adaptive flood risk management can reduce or delay initial and often large investment costs associated with infrastructure construction which may subsequently become unnecessary under future states of the world. There are two adaptive approaches which have been applied to flood risk management: (1) Dynamic Adaptive Policy Pathways (Haasnoot et al. 2013) and (2) real options analysis (e.g., Hino and Hall, 2017). These adaptive approaches should be combined with robustness-based approaches to promote design under non-stationarity from climate change.

Declaration of interests

None.

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